Visual Navigation - SARE Mission

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Abstract

The SARE Mission is for Earth Observation over Argentina. Only part of the orbit will be fully operative. To reduce cost, mass and volume, the same camera used to acquire the images will be used for attitude determination. The algorithm and methodology are explained in the present paper.

1. Introduction

All of the satellites are subject to some optimization process. Usually the safety by reducing the single point of failure is the most common of these criteria for medium and large spacecraft. Instead, the small and micro satellite community uses different paradigm: reducing total cost. To achieve this goal, different strategies have been used along the last decade. Some of them are based in reducing the launching mass, or by shortcutting the development time. All of these ways increase the risk of catastrophic failure without on board mitigation. It is the typical issue in the small satellite industry.

The visual navigation methodology is addressed in the same direction we have mentioned above: the cost reduction of the attitude control subsystem, by reusing the image data of one of the optical cameras to be used for attitude and orbit determination in addition to its specific purpose.

In general the optical payload is powered ON during part of the orbit, typically over the country owner of the satellite. The precise attitude and orbit knowledge

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are necessary to geo-localize the images during this portion of the orbit. For the rest of the time, a coarse knowledge of the spacecraft orientation and positioning is accepted. This information can be taken from a tri-axial magnetometer, coarse sun sensors and/or cheap gyroscopes. The small portion of mass, volume, cost and power required for this set of sensors allows to count with them even in micro satellites.

The usual procedure is as follows: the optical camera acquires the visible image; the steam of bytes is stored in the mass memory, one or several X-Band transmitter downloads the payload data when the satellite passes over the ground station.

The proposed method consists in using the same information (image) to calculate attitude and positioning of the spacecraft at the time the image was acquired.

Basically, the image is sent to the attitude control electronics (ACE) in addition to the normal path, which is the mass memory destination. The image may contain areas without information, such as clouds, sea, wider rivers, snows, etc, which can be detected by comparing the saturation level of each pixel with the background. It is expected that just one part of the image can be used as attitude-orbit sensor.

It is interesting a brief discussion about this issue. As the presence of clouds does not allow the calculation of the satellite orientation, no information is extracted. From the science or application point of view, this image does not give any practical information, so it is not required a precise attitude-orbit calculation.

The image data is accompanied in almost all of the cases with the output of the on board sensors (magnetometers, coarse sun sensors, gyros, etc.), which supply an approximate solution for the orbit location and the attitude determination. The ongoing process is highly simplified by using this information, but the computation should be able to work without any external aid.

With reference to the new method, there are two steps to be considered:

1. Determination of the active area. The determination is made under three different points of view: spectral and spatial analysis and the level of saturation of each pixel.

2. Determination of the called *keypoints* for a given image. These *especial features* allow to identify the image even at different orientation and/or scales.

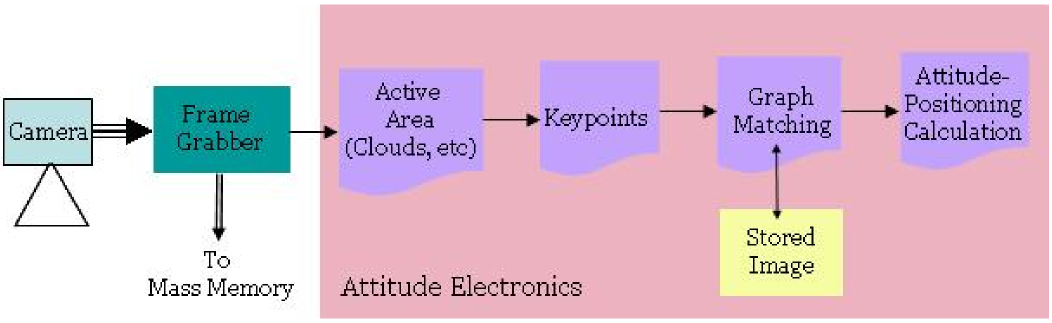

Figure 1: General Block Diagram.

3. Processing of these keypoints to compare them with the same contained in a database in the EEPROM memory.
4. Based in this descriptor, the attitude and orbit is computed.

The following section takes into account each of the above steps.

2. Image Descriptors

After determining the active area of the incoming image by canceling the area covered by clouds, by sea, etc, it is desirable to express the total image by a set of simple descriptors called keypoints. These points play the same role than the stars for the star tracker sensor: they have an unique geometry, which allows to identify the attitude when compared with a known pattern. The extraction feature is the most important step for invariant pattern recognition. This descriptor should accomplish the following characteristics:

1. **Shift Invariance**: In systems theory, a transform is shift invariant iff the transformation operator commutates with the shift operator. The magnitude Fourier Transform is an example of shift-invariant transform. From another point of view, a transformation is shiftable iff the coefficient energy in each transform subband is conserved under input-signal shifts. A transformation is shift sensitive because an input-shift generates unpredictable changes in the descriptor coefficients.
2. **Rotation Invariance**: If the function is rotated an angle, the descriptor coefficients are rotated the same angle. Fourier Transform is a good

example of rotation invariant.

3. **Scale Invariant**: This property is very important in case of having image at different altitudes. It is expected that global descriptors like Fourier Transform can be affected in their coefficients by a local variation.

The selected descriptor should be invariant to translation, rotation and scaling to be used in real time on board a satellite. The discrete Fourier Transform and the Wavelets Transform have been analyzed as potential representation of the image.

2.1. Fourier Transform

A continuous function can be approximated by samples and the approximation of the Fourier integral by the discrete Fourier Transform requires applying a matrix whose order is the number of sample points n. If the samples are uniformly spaced, then the Fourier matrix can be factored into a product of just a few sparse matrices, and the resulting factors can be applied to a vector in an arithmetic operation of total order $\mathrm{O}\left(n \log_2 n\right)$. This is the so-called Fast Fourier Transform (FFT). By defnition the FFT is translation invariant. The rotation invariance is obtained by transforming the image representation from Cartesian to Polar coordinates. It is clear that the rotation in polar frame is a translation. A second FFT over the polar represented image gives the desired descriptor for pattern recognition. This process is highly computationally expensive.

2.2. Wavelets Transform

The wavelets are functions that satisfy certain mathematical requirements. The fast wavelet transform is actually more computationally efficient than the FFT: for the same length, n, t requires approximately $\mathrm{O}\left(n\right)$ operations. It is well known that the ordinary discrete wavelets transform is not shift invariant, because the decimation operation during the transform. This is the main limitation in pattern recognition. Kingsbury in ((**?**)), introduced a new kind of wavelets transform, called the Dual Tree Complex Wavelets Transform (DTCWT) that exhibits approximate shift invariant property and improved angular resolution. The DTCWT can be successfully used in invariant feature extraction for pattern recognition.

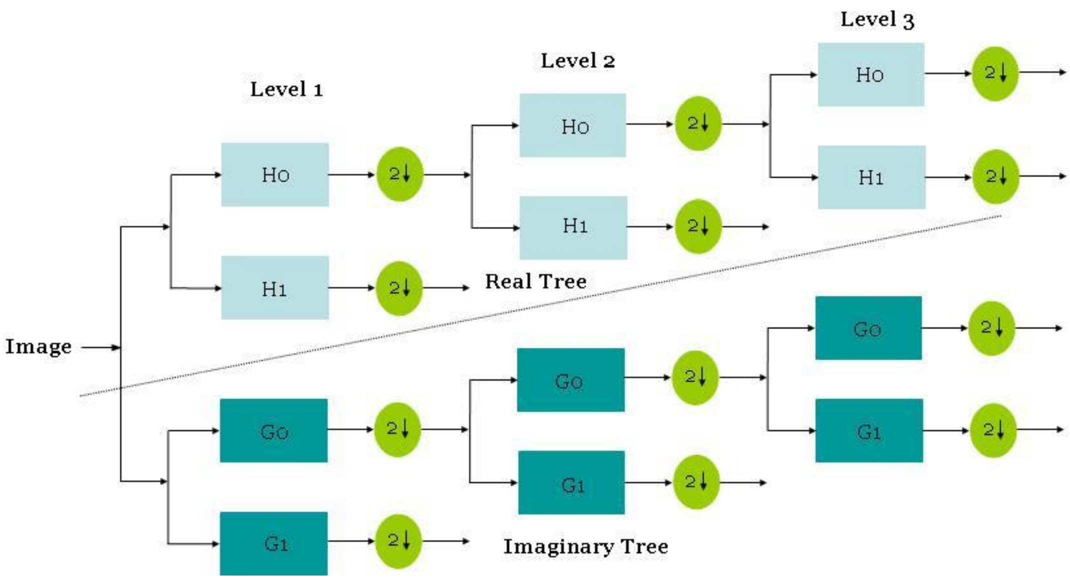

Figure 2: Wavelets Decomposition

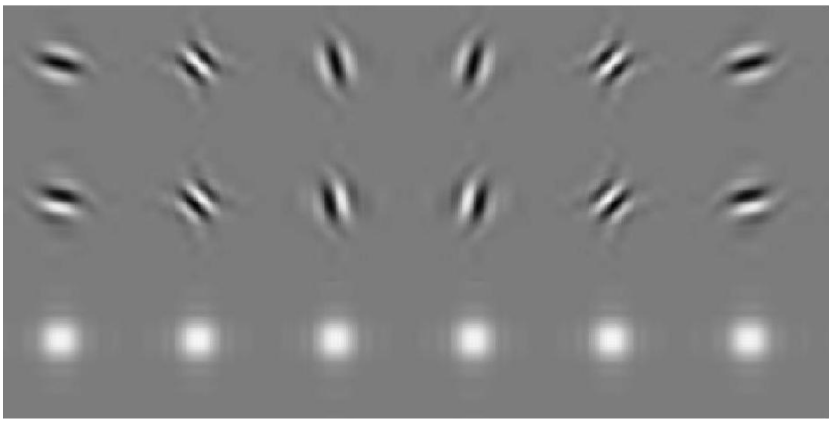

Figure 3: Twelve wavelets associated with the Dual Tree Wavelets. The angles are 15°, 45°, 75°, 105°, 135°, 165°.

2.3. Keypoint Detection

. We mean typically blobs, junctions and corners when refering to keypoints. Wavelets transform provides a powerful framework to decompose image into different scales and orientations. The DTCWT are the ideal candidate for multiscale, robust and computationally efficient keypoint detection, which are desirable properties for visual recognition tasks.

In the approach described in ((4)) the keypoint energy measured from the decimated DTCWT coefficients at different scales is accumulated into a single smooth energy map. This accumulated map plays key role since its peaks define the keypoint location and its gradient is used to derive the keypoint scales.

Given an image of $w \times h$ pixels, the DTCWT decomposition results in a decimated dyadic decomposition $s = 1, \ldots\, m$ scales, where each scale is of size $\frac{w}{2^s} \times \frac{h}{2^s}$. At each decimated location of each scale, we have a set C of 6 complex coefficients corresponding to responses to the 6 subband orientations, namely 15°, 45°, 75°, 105°, 135°, 165°. The directional information is useful to design a keypoint energy measure that emphasises the presence of a keypoint while ignoring edges and uniform areas. Fauquer at al. introduced the following keypoint energy measure that we propose based on the product of all six subbands magnitudes:

$$E(C) = \alpha^s \left(\prod_{b=1}^{6} \rho_b \right)^{\beta} \tag{1}$$

where α is set to 1 and $\beta = 1.4$ following ((4)). Under these calculations m decimated energy maps $M_1, \ldots, M_m$ are produced by calculating $E(C)$ for all the coefficients at each scale of the DTCWT decomposition. To obtain accurate keypoint localization from the decimated maps M_s the procedure suggested by Fauqueur, et. al. is copied below for simplicity.

Let $f_s\left(M_s\right)$ be the 2D Gaussian kernel interpolation up to the original image size. Let us define the *accumulated energy map* of the image as the sum of the interpolated maps from scales 1 to m

$$A = \sum_{s=1}^{m} f_s\left(M_s\right) \tag{2}$$

It is defined the keypoint locations as the peak location in A, by simple detecting where energy values in A are maximum on a 3 $\times$ 3 neighborhood.

3. Matching Graphs

After the keypoints have been determined, the next step in our algorithm is the calculation of the mismatching between the incoming image and one of the stored ones. To this end, the set of keypoints are used to create weighted finite graphs. This process of matching graphs is a NP-complete problem, which is a clear indication of the computational effort with a reasonable number of keypoints.

In ((3)) the algorithm to match two graphs: G and g is described. Both graphs may be sparse and whose links may take values in $\mathbb{R}$, the match matrix M is selected to minimized the following objective function,

$$E_{wg}(M) = -\frac{1}{2} \sum_{a=1}^{A} \sum_{i=1}^{I} \sum_{b=1}^{A} \sum_{j=1}^{I} M_{ai}\, M_{bj}\, C_{aibj} \tag{3}$$

where, A and I are the nodes respectively and C_{aibj} is defined as, $C_{aibj} = 0$ if either G_{ab} or g_{ij} is null or $C_{aibj} = 0(G_{ab}, g_{ij})$ otherwise. The G_{ab} and g_{ij} are the adjacency matrices of the graphs, whose elements may be in $\mathbb{R}$. The function $c(.,.)$ is chosen as a measure of the compatibility between the links of the two graphs. The matrix M indicates which nodes in the two graphs match, $M_{ai} = 1$ if node a in G corresponds to node i in g, and $M_{ai} = 0$ otherwise.

This algorithm is $O(lm)$ with l and m the number of elements of each graph. The asymptotic order is appropriated for our application. The algorithm presented in ((**?**)) is implemented.

4. Separating Orbit Positioning and Attitude Errors

After the graph matching process is finished, between the incoming and the stored images, the attitude error and orbit positioning error should be calculated.

In order to separate the ephemeris error from the attitude error as much as possible, we should first use the most precise ephemeris data available and correct systematic errors with available models. The presence of GPS receiver is highly desired on board. Second we should use available a priori information in addition to the observation to cure the ill-condition of the normal equation in statistical estimation.

This problem can be solved from different approaches. In general we have the observation equation,

$$\mathbf{Y} = H\,\mathbf{X} + \epsilon \tag{4}$$

with $E\,[\epsilon] = \mathbf{0}$, and $\mathrm{Cov}[\epsilon] = s^2\,C$. The a priori information of the parameter is given by

$$\mathbf{x} = \mathbf{X} + \epsilon_x \tag{5}$$

with $E\,[\epsilon_x] = \mathbf{0}$, and $\mathrm{Cov}[\epsilon_x] = q^2\,C_x$.

The BLUE estimator $\hat{\mathbf{x}}$ can be calculated as,

$$\left(s^{-2}\,H\,C^{-1}\,H + q^{-2}\,C_x^{-1}\right)\,\hat{\mathbf{x}} = \left(s^{-2}\,H\,C^{-1}\right)\,\mathbf{Y} + \left(q^{-2}\,H\,C_x^{-1}\right)\,\mathbf{X} \tag{6}$$

with a covariance matrix of,

$$\mathrm{Cov}\,[\hat{\mathbf{x}}] = \left(s^{-2}\,H\,C^{-1}\,H + q^{-2}\,C_x^{-1}\right)^{-1} \tag{7}$$

5. Conclusion

The optical camera plus an appropriate algorithm running in the AOCS computer allows to replace or at least be a backup for the star tracker in some Earth observation missions. The software explained in this paper is conceptually complex, but the implementation can be done in simple electronics cards such a FPGA device. The attitude and orbit solution is under normal circumstances computed each 5 seconds, wich is enough for this kind of application.

References

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